Chapter 6

Stopping criteria, adaptivity, accelerations

Convex Optimization for Computer Vision

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Customized proximal point algorithms

Structured optimization methods for

$$\min_u G(u) + F(Ku)$$

under the assumption of F and G being simple or - in the ADMM case - $(\partial G + \frac{1}{\tau} K^T K)^{-1}$ being easy to compute.

Goal: Find pair $(\hat{u}, \hat{p})$ with

$$-K^T \hat{p} \in \partial G(\hat{u}), \quad K\hat{u} \in \partial F^*(\hat{p})$$

Primal Dual-Hybrid Gradient (PDHG) method:

$$0 \in \begin{bmatrix} \partial G & K^T \\ -K & \partial F^* \end{bmatrix} \begin{bmatrix} u^{k+1} \\ p^{k+1} \end{bmatrix} + \begin{bmatrix} \frac{1}{\tau} I & -K^T \\ -K & \frac{1}{\sigma} I \end{bmatrix} \begin{bmatrix} u^{k+1} - u^k \\ p^{k+1} - p^k \end{bmatrix}$$

What is a good stopping criterion?

Stopping customized proximal point algorithms

Generic form:

$$0 \in \begin{bmatrix} \partial G & K^T \\ -K & \partial F^* \end{bmatrix} \begin{bmatrix} u^{k+1} \\ p^{k+1} \end{bmatrix} + \underbrace{\begin{bmatrix} M_1 & -K^T \\ -K & M_2 \end{bmatrix}}_{=:M} \begin{bmatrix} u^{k+1} - u^k \\ p^{k+1} - p^k \end{bmatrix}$$

such that the matrix M is positive (semi-)definite.

Natural considerations:

- How close is $-K^T p^{k+1}$ to being an element of $\partial G(u^{k+1})$?
- How close is $K u^{k+1}$ to being an element of $\partial F^*(p^{k+1})$?

We define the ***primal** and **dual** residuals*:

$$\begin{aligned} r_p^{k+1} &= M_2(p^{k+1} - p^k) - K(u^{k+1} - u^k) \\ r_d^{k+1} &= M_1(u^{k+1} - u^k) - K^T(p^{k+1} - p^k) \end{aligned}$$

Primal and dual residuals

Based on the ***primal*** *and* ***dual*** *residuals*:

$$r_p^{k+1} = M_2(p^{k+1} - p^k) - K(u^{k+1} - u^k)$$
$$r_d^{k+1} = M_1(u^{k+1} - u^k) - K^T(p^{k+1} - p^k)$$

we could consider our algorithm to be convergent if $\|r_d^{k+1}\|^2 + \|r_p^{k+1}\|^2 \to 0$, because this implies

$$\text{dist}(-K^T p^{k+1}, \partial G(u^{k+1})) \to 0,$$
$$\text{dist}(K u^{k+1}, \partial F^*(p^{k+1})) \to 0.$$

Note that this notion of convergences does not imply convergence of u^k and p^k yet!

Nevertheless, we know PDHG and ADMM do converge, and $\|r_d^{k+1}\|$ and $\|r_p^{k+1}\|$ are good measures for convergence!

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Upper bounds on the residuals

How should we use $\|r_d^{k+1}\|$ and $\|r_p^{k+1}\|$ to formalize a stopping criterion?

- Simple option: Iterator until $\|r_d^{k+1}\| \leq \epsilon$ and $\|r_p^{k+1}\| \leq \epsilon$.
- Could be unfair, if $u^k \in \mathbb{R}^n$ and $p^k \in \mathbb{R}^m$ and e.g. $n >> m$. Use $\|r_d^{k+1}\| \leq \sqrt{n}\,\epsilon$ and $\|r_p^{k+1}\| \leq \sqrt{m}\,\epsilon$.
- Could be unfair for different scales! Introduce absolute and relative error criteria:

$$\begin{aligned}\|r_d^{k+1}\| &\leq \sqrt{n}\,\epsilon^{abs} + \text{dual scale factor} \cdot \epsilon^{rel}\\ \|r_p^{k+1}\| &\leq \sqrt{m}\,\epsilon^{abs} + \text{primal scale factor} \cdot \epsilon^{rel}\end{aligned}$$

But what are reasonable scale factors?

Scaling the primal residuum

The primal residual

$$r_p^{k+1} = M_2(p^{k+1} - p^k) - K(u^{k+1} - u^k)$$

measures how far Ku^{k+1} is away from a particular element in $\partial F^*(p^{k+1})$, and therefore scales with the magnitude of elements in $\partial F^*(p^{k+1})$.

More precisely:

$$\begin{aligned} & 0 \in \partial F^*(p^{k+1}) - Ku^{k+1} + r_p^{k+1} \\ \Rightarrow & 0 \in \partial F^*(p^{k+1}) - K^T(2u^{k+1} - u^k) + M_2(p^{k+1} - p^k). \\ \Rightarrow & \underbrace{M_2(p^k - p^{k+1}) + K^T(2u^{k+1} - u^k)}_{=:z^{k+1}} \in \partial F^*(p^{k+1}) \end{aligned}$$

Thus, we can use

$$\|r_p^{k+1}\| \leq \sqrt{m}\, \epsilon^{abs} + \|z^{k+1}\| \cdot \epsilon^{rel}$$

to be scale-independent.

Scaling the dual residuum

The dual residual

$$r_d^{k+1} = M_1(u^{k+1} - u^k) - K^T(p^{k+1} - p^k)$$

measures how far $-K^T p^{k+1}$ is away from a particular element in $\partial G(u^{k+1})$, and therefore scales with the magnitude of elements in $\partial G(u^{k+1})$.

More precisely:

$$\begin{aligned} & 0 \in \partial G(u^{k+1}) + K^T p^{k+1} + r_d^{k+1}. \\ \Rightarrow\ & 0 \in \partial G(u^{k+1}) + K^T p^k + M_1(u^{k+1} - u^k) \\ \Rightarrow\ & \underbrace{M_1(u^k - u^{k+1}) - K^T p^k}_{=:v^{k+1}} \in \partial G(u^{k+1}) \end{aligned}$$

Thus, we can use

$$\|r_d^{k+1}\| \leq \sqrt{n}\, \epsilon^{abs} + \|v^{k+1}\| \cdot \epsilon^{rel}$$

to be scale-independent.

A scaled absolute and relative stopping criterion

In summary, a good stopping criterion is

$$\|r_p^{k+1}\| \leq \sqrt{m}\, \epsilon^{abs} + \|z^{k+1}\| \cdot \epsilon^{rel},$$
$$\|r_d^{k+1}\| \leq \sqrt{n}\, \epsilon^{abs} + \|v^{k+1}\| \cdot \epsilon^{rel}.$$

Interesting observation in our previous considerations: ADMM, Douglas Rachford, PDHG, and any other ”customized proximal point” algorithm actually generates iterates $(u^{k+1}, p^{k+1}, v^{k+1}, z^{k+1})$ with

$$v^{k+1} \in \partial G(u^{k+1}), \qquad z^{k+1} \in \partial F^*(p^{k+1}).$$

The goal of all algorithms is to achieve convergence

$$\| \underbrace{z^{k+1} - Ku^{k+1}}_{=r_p^{k+1}} \| \rightarrow 0 \text{ and } \| \underbrace{v^{k+1} + K^T p^{k+1}}_{=r_d^{k+1}} \| \rightarrow 0!$$

Note that z is exactly the ”split” variable in the augmented Lagrangian based derivation of ADMM!

Adaptive stepsizes

r_p^{k+1} and r_d^{k+1} determine the convergence of the algorithm.

Can we also use r_d and r_p to accelerate the algorithm?

Adaptive stepsizes:

$$0 \in \begin{bmatrix} \partial G & K^T \\ -K & \partial F^* \end{bmatrix} \begin{bmatrix} u^{k+1} \\ p^{k+1} \end{bmatrix} + \begin{bmatrix} \frac{1}{\tau^k} M_1 & -K^T \\ -K & \frac{1}{\sigma^k} M_2 \end{bmatrix} \begin{bmatrix} u^{k+1} - u^k \\ p^{k+1} - p^k \end{bmatrix}$$

Base the choices of τ^k and σ^k on the residuals r_p^k and r_d^k?

Residual balancing

First option: Residual balancing! Let $(M_1, -K^T; -K, M_2)$ be positive definite. Pick τ^0 and σ^0 with $\tau^0\sigma^0 < 1$ as well as $\mu > 1$, $\alpha > 1$:

- If $\|r_p^k\| > \mu\|r_d^k\|$, do

$$\tau^{k+1} = \frac{1}{\alpha}\tau^k, \quad \sigma^{k+1} = \alpha\sigma^k$$

- If $\|r_d^k\| > \mu\|r_p^k\|$, do

$$\tau^{k+1} = \alpha\tau^k, \quad \sigma^{k+1} = \frac{1}{\alpha}\sigma^k$$

- Keep $\tau^{k+1} = \tau^k$ and $\sigma^{k+1} = \sigma^k$ otherwise.

Why could this make sense?

Unbalanced adaption

Second option: Fougner, Boyd '15: Let $(M_1, -K^T; -K, M_2)$ be positive definite. Pick τ^0 and σ^0 with $\tau^0\sigma^0 < 1$ as well as $\mu > 1$, $\alpha > 1$:

- If $\|r_d^k\| < \epsilon^{thresh}$ and $k > \mu k_1^{prev}$, do

$$\tau^{k+1} = \frac{1}{\alpha}\tau^k, \quad \sigma^{k+1} = \alpha\sigma^k, \quad k_1^{prev} \leftarrow k.$$

- If $\|r_p^k\| < \epsilon^{thresh}$ and $k > \mu k_2^{prev}$, do

$$\tau^{k+1} = \alpha\tau^k, \quad \sigma^{k+1} = \frac{1}{\alpha}\sigma^k, \quad k_2^{prev} \leftarrow k.$$

- Keep $\tau^{k+1} = \tau^k$ and $\sigma^{k+1} = \sigma^k$ otherwise.

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Convergence guarantees?

The previous two adaptive step size methods are heuristics that work well in practice.

In general, they have no convergence guarantees!

Common trick: Changing the parameters finitely many times only, reestablishes the convergence guarantees!

More appealing from a theoretical point of view: Decreasing the adaptivity of the stepsizes fast enough.

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Convergence guarantees with adaptive step sizes

Goldstein et al. 2015

Consider $M_1 = \frac{1}{\tilde{\tau}} I$, $M_2 = \frac{1}{\tilde{\sigma}} I$ with $\tilde{\sigma}\tilde{\tau} < \|K\|^2$, and define

$$\delta^k = \min\left\{ \frac{\tau^{k+1}}{\tau^k}, \frac{\sigma^{k+1}}{\sigma^k}, 1 \right\}, \quad \phi^k = 1 - \delta^k$$

Let the following three conditions hold:

1. The sequences $\{\tau^k\}$, $\{\sigma^k\}$ remain bounded.
2. The sequence ϕ^k is summable.
3. It holds that $\tau^k \sigma^k < c < 1$.

Then the resulting adaptive PDHG algorithm converges.

Conjecture (for you to prove)

The same result holds for arbitrary M_1, M_2 provided that the matrix $(M_1, -K^T; -K, M_2)$ is positive definite.

Customized proximal point algorithms

Decreasing residual balancing: Let $(M_1, -K^T; -K, M_2)$ be positive definite. Pick τ^0 and σ^0 with $\tau^0\sigma^0 < 1$. Further choose $\mu > 1$, $\alpha^0 < 1$, $\beta < 1$ and adapt as follows

- If $\|r_p^k\| > \mu \|r_d^k\|$, do

$$\tau^{k+1} = (1-\alpha^k)\tau^k, \quad \sigma^{k+1} = \frac{1}{1-\alpha^k}\sigma^k, \quad \alpha^{k+1} = \alpha^k \cdot \beta.$$

- If $\|r_d^k\| > \mu \|r_p^k\|$, do

$$\tau^{k+1} = \frac{1}{1-\alpha^k}\tau^k, \quad \sigma^{k+1} = (1-\alpha^k)\sigma^k, \quad \alpha^{k+1} = \alpha^k \cdot \beta.$$

- Keep $\tau^{k+1} = \tau^k$, $\sigma^{k+1} = \sigma^k$, and $\alpha^{k+1} = \alpha^k$ otherwise.

Convergence proof based on previous theorem.

Sketch of proof

Sketch of the proof:

- The product $\tau^k \sigma^k$ does not change, thus 3. holds.
- It holds that

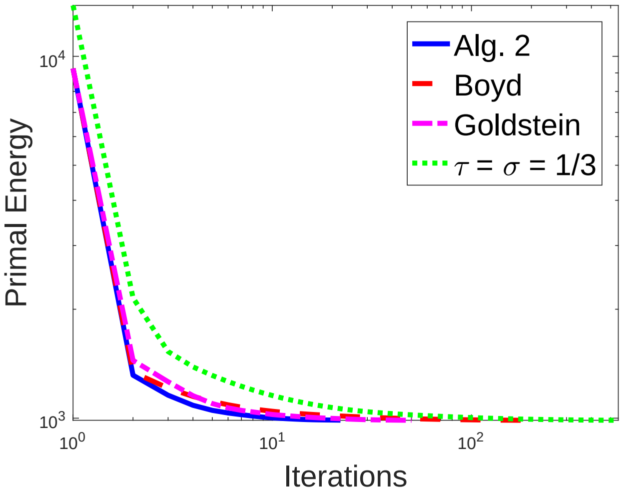
$$\phi^k = \begin{cases} 0 & \text{if stepsizes were not updated,} \\ \alpha^k & \text{if stepsizes were updated.} \end{cases}$$

  which means the j-th nonzero entry of $\{\phi^k\}$ is $(\alpha^0)^j$.
- $\sum_k \phi^k = \sum_{j \in I} (\alpha^0)^j < C$, thus condition 2 holds.
- Without restriction of generality we may drop those steps where the stepsize remained unchanged. We find

$$\tau^{j+1} \leq \frac{1}{1-\alpha^j}\tau^j \leq \left(\frac{1}{1-\alpha^j}\right)^j \tau^0 = \frac{1}{(1-\alpha^0\beta^j)^j}\tau^0$$

  The factor $(1-\alpha^0\beta^j)^j$ remains bounded from below and thus condition 1 follows. (For $x \geq -1$: $(1+x)^n \geq 1 + nx$)

Example plot of convergence for ROF model



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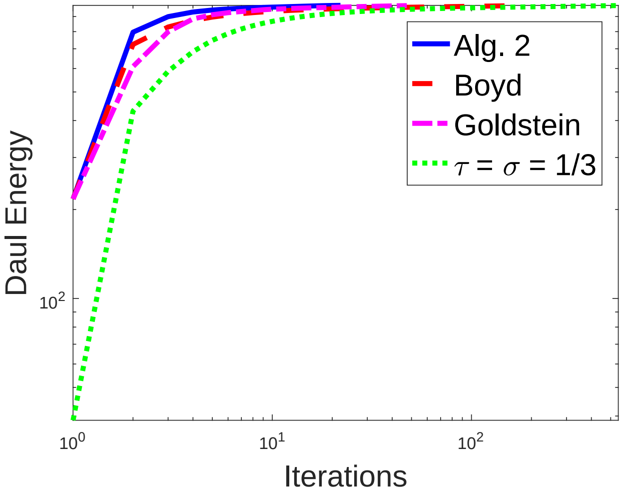

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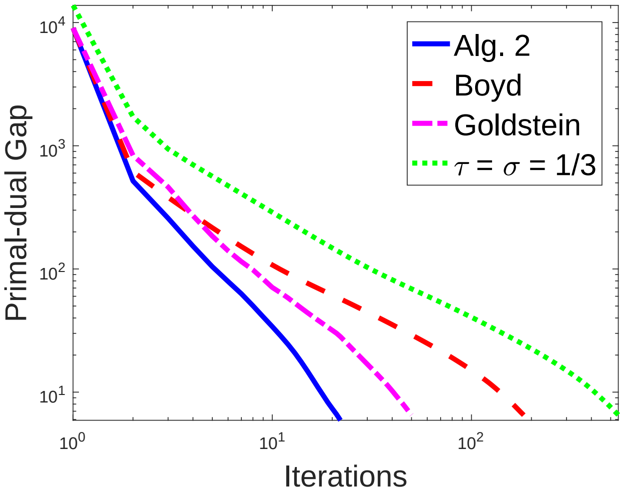

Backtracking

Condition 3 in the previous convergence result for adaptive stepsizes can also be weakened to

3. The saddle point problem

$$\min_u \max_p G(u) + \langle Ku, p \rangle - F^*(p)$$

restricts either u or p to a bounded set. Furthermore there exists a constant c such that for all $k > 0$

$$\left\langle \begin{bmatrix} u^{k+1} - u^k \\ p^{k+1} - p^k \end{bmatrix}, \begin{bmatrix} \frac{1}{\tau^k} M_1 & -K^T \\ -K & \frac{1}{\sigma^k} M_2 \end{bmatrix} \begin{bmatrix} u^{k+1} - u^k \\ p^{k+1} - p^k \end{bmatrix} \right\rangle$$

$$\geq c \left\langle \begin{bmatrix} u^{k+1} - u^k \\ p^{k+1} - p^k \end{bmatrix}, \begin{bmatrix} \frac{1}{\tau^k} M_1 & 0 \\ 0 & \frac{1}{\sigma^k} M_2 \end{bmatrix} \begin{bmatrix} u^{k+1} - u^k \\ p^{k+1} - p^k \end{bmatrix} \right\rangle.$$

Under this condition the convergence result still holds.

Backtracking

The stability condition 3 from the previous slide can used to define a *backtracking* algorithm that works without knowing the constant $\|K\|^2$.

Define

$$b^k = \frac{2\tilde{\tau}\tilde{\sigma}\tau^k\sigma^k\langle p^{k+1} - p^k, K(u^{k+1} - u^k)\rangle}{\gamma\tilde{\sigma}\sigma^k\|u^{k+1} - u^k\|^2 + \gamma\tilde{\tau}\tau^k\|p^{k+1} - p^k\|^2}$$

for some $\gamma \in]0, 1[$.

If $b^k \leq 1$ keep iterating, if $b^k > 1$ update

$$\tau^{k+1} = \beta\tau^k / b^k, \quad \sigma^{k+1} = \beta\sigma^k / b^k$$

for $\beta \in]0, 1[$.

Key insight to prove convergence: $b^k > 1$ can only happen finitely many times.